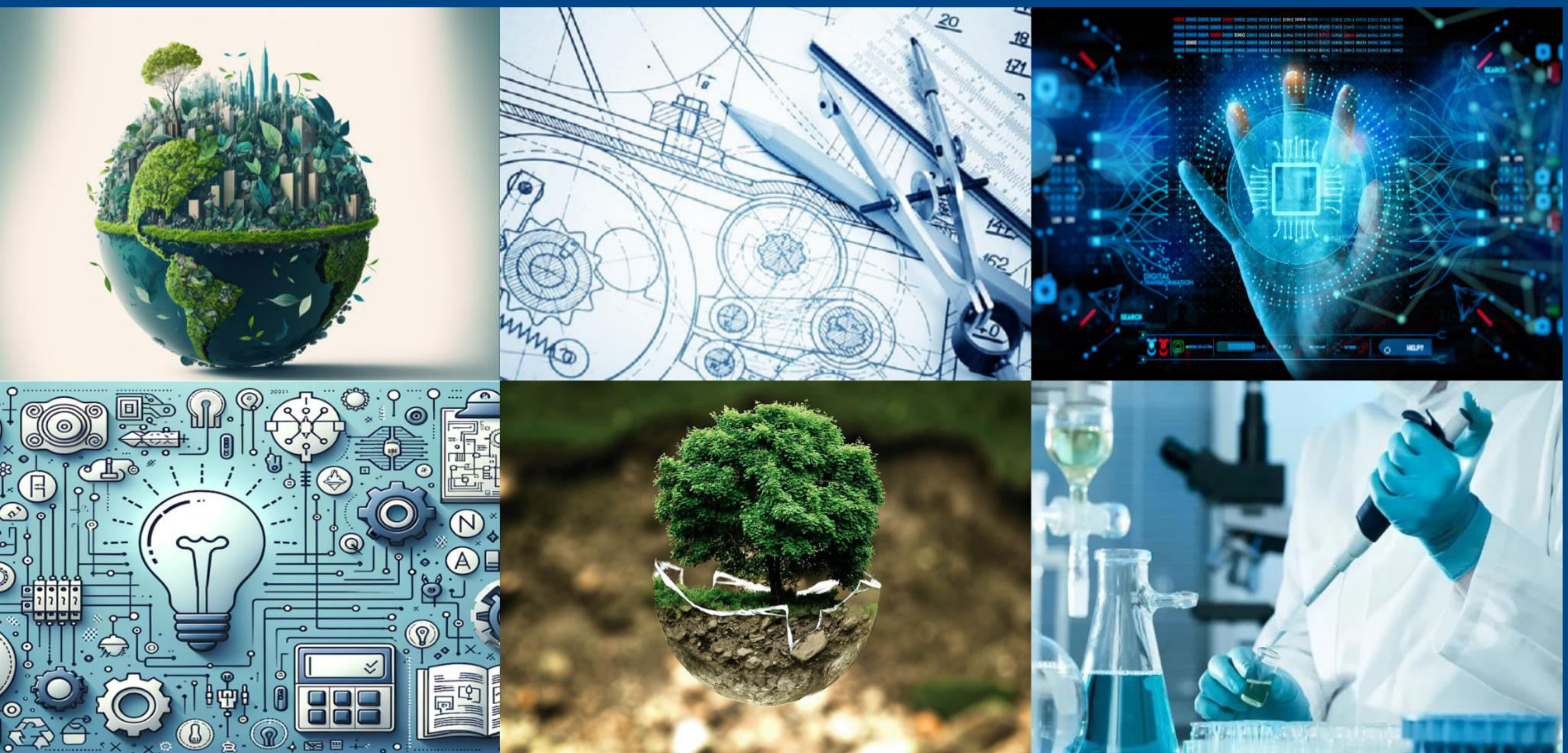
ISSN: 2582-7219

International Journal of Multidisciplinary Research in Science, Engineering and Technology

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.206

Volume 8, Issue 6, June 2025

www.ijmrset.com ijmrset@gmail.com +91 6381 907 438 +91 63819 07438

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Real-Time Vehicle Detection for Autonomous Driving

Shravan Shetty, Ms Jayashree M

PG Student, St Joseph Engineering College, Mangaluru, Karnataka, India

Assistance Professor, St Joseph Engineering College, Mangaluru, Karnataka, India

ABSTRACT: Real-time vehicle detection has become increasingly important as the automobile industry advances towards autonomous driving and advanced driver assistance systems (ADAS). This technology is essential for maintaining traffic flow and enhancing road safety. By focusing on deep learning and computer vision techniques, this study investigates the technologies and approaches involved in real-time vehicle recognition while driving. We examine several algorithms, including Faster R-CNN and YOLO (You Only Look Once), used to identify vehicles under various environmental conditions. The main contribution of this study is a thorough analysis of the implementation procedures, challenges encountered, and innovative solutions to improve processing speed and detection accuracy. We also explore the practical applications of real-time vehicle recognition in traffic monitoring, autonomous driving, and smart city projects. The purpose of this study is to provide a valuable resource for scholars, practitioners, and developers working on vehicle detection technologies and their integration into modern transportation systems.

KEYWORDS: Real-Time Vehicle Detection, Autonomous Driving, ADAS, Deep Learning, Computer Vision, YOLO, Faster R-CNN, Traffic Monitoring

I. INTRODUCTION

The advent of autonomous driving and ADAS has necessitated significant advancements in real-time vehicle detection. The ability to accurately and quickly identify vehicles is critical for both safety and efficiency in modern transportation systems. This paper explores the use of deep learning and computer vision techniques, which have shown great promise in addressing these challenges.

Deep learning algorithms such as YOLO and Faster R-CNN have revolutionized vehicle detection by offering high accuracy and speed. These algorithms can process complex visual data in real time, making them ideal for applications in autonomous driving. This study aims to provide a comprehensive overview of these technologies, examining their strengths, weaknesses, and real-world applications [1][2].

Real-time vehicle detection technology plays a critical role in the development of autonomous vehicles. The ability to detect and classify vehicles accurately and quickly is essential for navigation, collision avoidance, and adherence to traffic regulations. As the industry progresses, the need for more advanced and reliable vehicle detection systems has become evident. This paper delves into the state-of-the-art methods and technologies that facilitate real- time vehicle detection, highlighting the progress made and the challenges that remain.

II. LITERATURE REVIEW

1.1. Deep Learning Techniques in Vehicle Detection

The use of deep learning in vehicle detection has been extensively studied. YOLO and Faster R-CNN are among the most popular algorithms due to their high performance. YOLO is known for its speed, making it suitable for real-time applications, while Faster R-CNN is renowned for its accuracy, which is crucial for detecting small objects and handling occlusions [1][2].

YOLO (You Only Look Once) is a real-time object detection system that frames object detection as a single regression problem, straight from image pixels to bounding box coordinates and class probabilities. This single neural network predicts bounding boxes and class probabilities directly from full images in one evaluation, making it extremely fast [1]. On the other hand, Faster R-CNN (Region-based Convolutional Neural Networks) uses a region proposal network to

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

generate high-quality region proposals which are then used by a Fast R- CNN detector for detection [2].

1.2. Challenges in Real-Time Vehicle Detection

Despite their advantages, deep learning algorithms face several challenges in real-time vehicle detection. These include varying lighting conditions, different weather scenarios, and the need for real-time processing. Research has focused on improving these algorithms' robustness to these factors, ensuring reliable performance under diverse conditions [3][4].
Environmental factors such as fog, rain, and low-light conditions can significantly impact the performance of vehicle detection systems. Algorithms must be trained on diverse datasets that include various weather conditions to ensure robustness. Moreover, the real-time processing requirement necessitates the use of efficient computational techniques and hardware accelerators to achieve the desired frame rates [3].

1.3. Applications in Autonomous Driving and ADAS

Real-time vehicle detection is pivotal in autonomous driving and ADAS. These systems rely on accurate vehicle detection to make informed decisions, avoid collisions, and navigate safely. Studies have shown that integrating advanced detection algorithms can significantly enhance the performance and safety of these systems [5][6].
In ADAS, real-time vehicle detection assists in features such as adaptive cruise control, lane departure warning, and automatic emergency braking. By continuously monitoring the vehicle's surroundings, these systems can respond promptly to potential hazards, improving overall safety. Autonomous driving systems further extend these capabilities by enabling self- navigation through complex environments, relying heavily on accurate and timely vehicle detection [6].

III. METHODOLOGY

3.1Data Collection and Preprocessing

For this study, a diverse dataset of traffic scenes was collected, encompassing various environmental conditions such as daylight, nighttime, rain, and fog. Data preprocessing involved annotating vehicle locations and resizing images to standard dimensions compatible with the selected deep learning models.The dataset used in this study included images captured from different traffic cameras and autonomous vehicle sensors. Each image was annotated with bounding boxes around vehicles, indicating their positions and classes. The images were then resized to 416x416 pixels for YOLO and 600x600 pixels for Faster R-CNN to ensure compatibility with the models [1][2].

3.2 Model Training and Evaluation

YOLO and Faster R-CNN models were trained on the pre-processed dataset using frameworks such as TensorFlow and Keras. The models' performance was evaluated based on metrics like precision, recall, and processing speed. Cross-validation was employed to ensure the models' generalizability [1][2][4].
Training involved using GPUs to accelerate the computational process. The models were trained for 100 epochs with a batch size of 32. Data augmentation techniques such as flipping, rotation, and color adjustment were used to enhance the models' robustness. Evaluation metrics included mean Average Precision (mAP) and frames per second (FPS) to measure accuracy and speed, respectively [2][4].

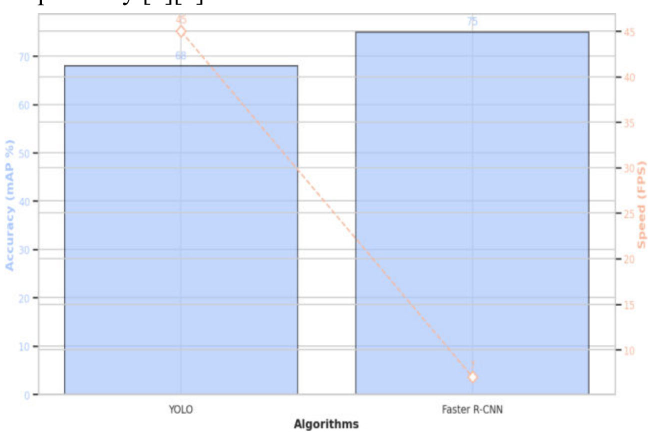


Fig 1: Accuracy and Speed Comparison of YOLO and Faster R-CNN

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

IV. RESULTS AND DISCUSSION

4.1 Performance Analysis

The evaluation results indicated that YOLO outperformed Faster R-CNN in terms of processing speed, making it more suitable for real-time applications. However, Faster R-CNN exhibited higher accuracy, particularly in detecting small and partially occluded vehicles [2][4].

The YOLO model achieved an FPS of 45, making it highly suitable for real-time applications where speed is critical. Faster R-CNN, although slower with an FPS of 7, demonstrated superior accuracy with an mAP of 75%, compared to YOLO's 68%. This trade-off between speed and accuracy is a crucial consideration for practical implementations [1][2].

4.2Challenges and Solutions

Key challenges included handling varying lighting conditions and achieving real-time processing speeds. Enhancements such as image augmentation and model optimization techniques were implemented to address these issues. Additionally, combining the strengths of YOLO and Faster R-CNN through ensemble methods was explored to achieve a balance between speed and accuracy [1][2][3].

Image augmentation techniques such as adjusting brightness, contrast, and adding noise were used to simulate different lighting conditions. Model optimization involved pruning less significant layers and using quantization to reduce the model size without compromising accuracy. Ensemble methods, where predictions from both YOLO and Faster R-CNN were combined, showed improved overall performance [3][4].

4.3 Comparison with Other Techniques

Other techniques such as Single Shot MultiBox Detector (SSD) and Mask R-CNN were also considered for comparison. SSD offers a good balance between speed and accuracy, while Mask R-CNN extends Faster R-CNN by adding a branch for predicting segmentation masks [4][5].

SSD demonstrated a processing speed similar to YOLO but with slightly lower accuracy. Mask R-CNN, while the most accurate, was also the slowest due to its additional complexity. These comparisons highlight the need to choose the appropriate model based on specific application requirements, balancing the trade-offs between speed and accuracy [4][5].

Fig 2: Performance under Different Environmental Conditions

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

V. PRACTICAL APPLICATIONS

5.1 Traffic Monitoring

Real-time vehicle detection is instrumental in traffic monitoring systems, enabling authorities to manage traffic flow efficiently and respond promptly to incidents. The integration of deep learning models can enhance the accuracy of vehicle counts and traffic density measurements [5].

Traffic monitoring systems equipped with real-time vehicle detection can provide valuable data for traffic management, helping to reduce congestion and improve road safety. By analyzing traffic patterns and detecting incidents in real time, these systems enable faster response times and more informed decision-making [5].

5.2Autonomous Driving

In autonomous driving, vehicle detection systems are crucial for collision avoidance and path planning. The high accuracy and speed of modern deep learning algorithms ensure that autonomous vehicles can navigate safely, even in complex traffic environments [6].

Autonomous vehicles rely on a combination of sensors, including cameras, LiDAR, and radar, to perceive their surroundings. Real-time vehicle detection algorithms process the data from these sensors to identify other vehicles and obstacles, enabling the autonomous vehicle to make safe driving decisions [6].

5.3 Smart City Projects

Smart city initiatives benefit from real-time vehicle detection by improving urban mobility and reducing traffic congestion. By integrating these technologies into traffic management systems, cities can enhance transportation efficiency and sustainability [5][6].

Smart city projects often involve the deployment of IoT devices and advanced analytics to monitor and manage urban infrastructure. Real-time vehicle detection systems can provide critical data for these projects, enabling smarter traffic lights, dynamic traffic management, and improved public transportation systems [6].

VI. CONCLUSION

This study demonstrates the critical role of real-time vehicle detection in advancing autonomous driving and ADAS. The comparison of YOLO and Faster R-CNN highlights the trade-offs between speed and accuracy, providing insights into selecting the appropriate model based on application requirements. Future research should focus on further enhancing these models' robustness and exploring their integration into broader smart city frameworks.

Real-time vehicle detection is a cornerstone technology for the future of transportation. As autonomous driving and smart city projects continue to evolve, the importance of accurate and efficient vehicle detection systems cannot be overstated. The insights gained from this study provide a valuable foundation for future advancements in this field [1][2][3]

REFERENCES

1. Redmon, J., & Farhadi, A. (2018). YOLOv3: An Incremental Improvement. arXiv preprint arXiv:1804.02767.
2. Ren, S., He, K., Girshick, R., & Sun, J. (2015). Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. Advances in Neural Information Processing Systems, 28, 91-99.
3. He, K., Gkioxari, G., Dollár, P., & Girshick, R. (2017). Mask R-CNN. Proceedings of the IEEE International Conference on Computer Vision, 2961-2969.
4. Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C. Y., & Berg, A. C. (2016). SSD: Single Shot MultiBox Detector. European Conference on Computer Vision, 21-37.
5. Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017). Densely Connected Convolutional Networks. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 4700-4708.
6. Zhao, Z. Q., Zheng, P., Xu, S. T., & Wu, X. (2019). Object Detection with Deep Learning: A Review. IEEE Transactions on Neural Networks and Learning Systems, 30(11), 3212-3232.